组会

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Retrieval-guided Dialogue Response Generation via a Matching-to-Generation Framework

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Motivation

seq2seq: safe question;

seq2seq + retrieval: collapses to vanilla seq2seq due to mismatch.

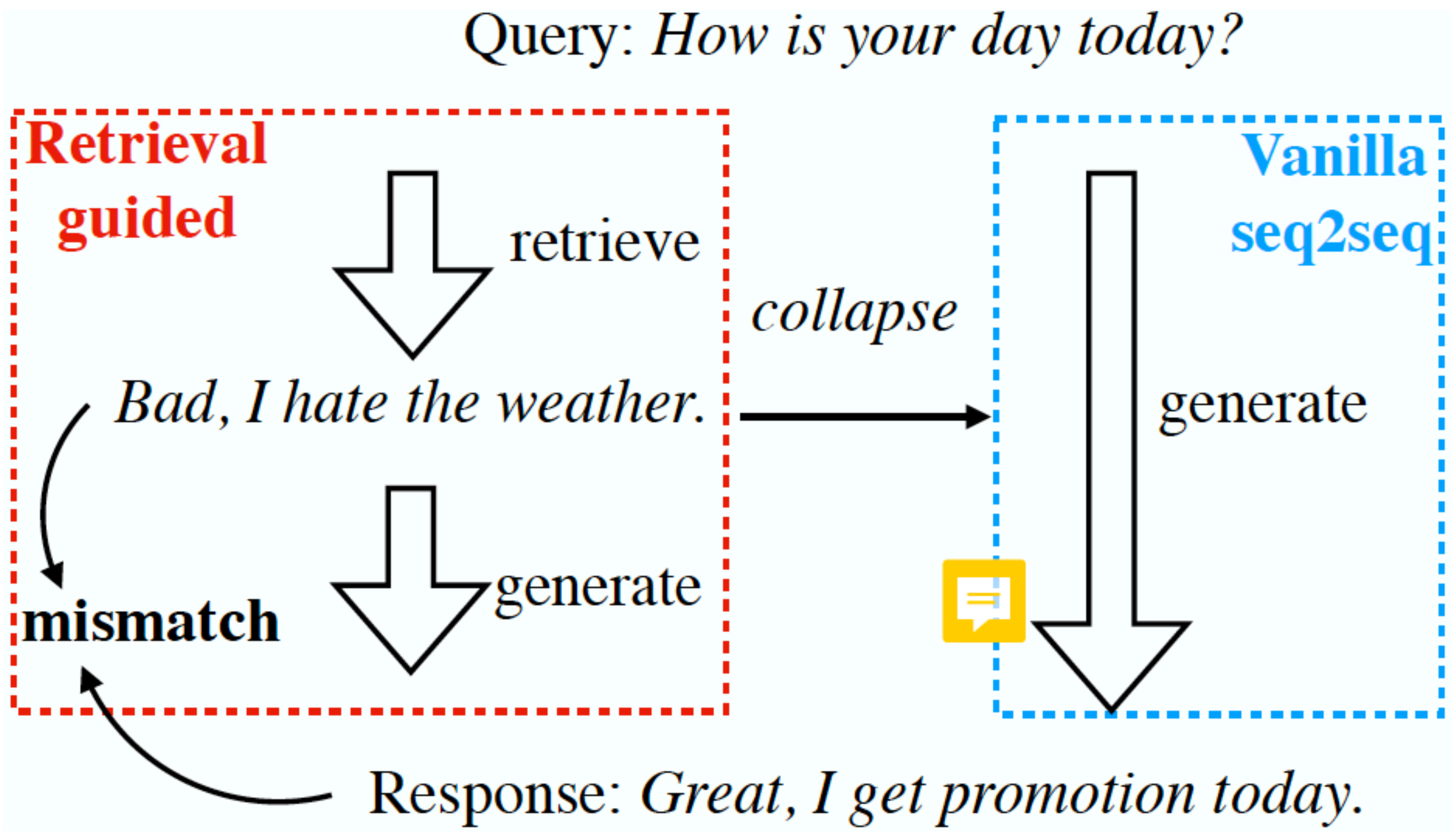


Figure 1: The common problem for training a retrieval-guided generation model in previous work. The model is forced to neglect the retrieved response even though it is a proper response, due to the mismatch between the retrieved response and the target response.

Model— —matching-to-generation

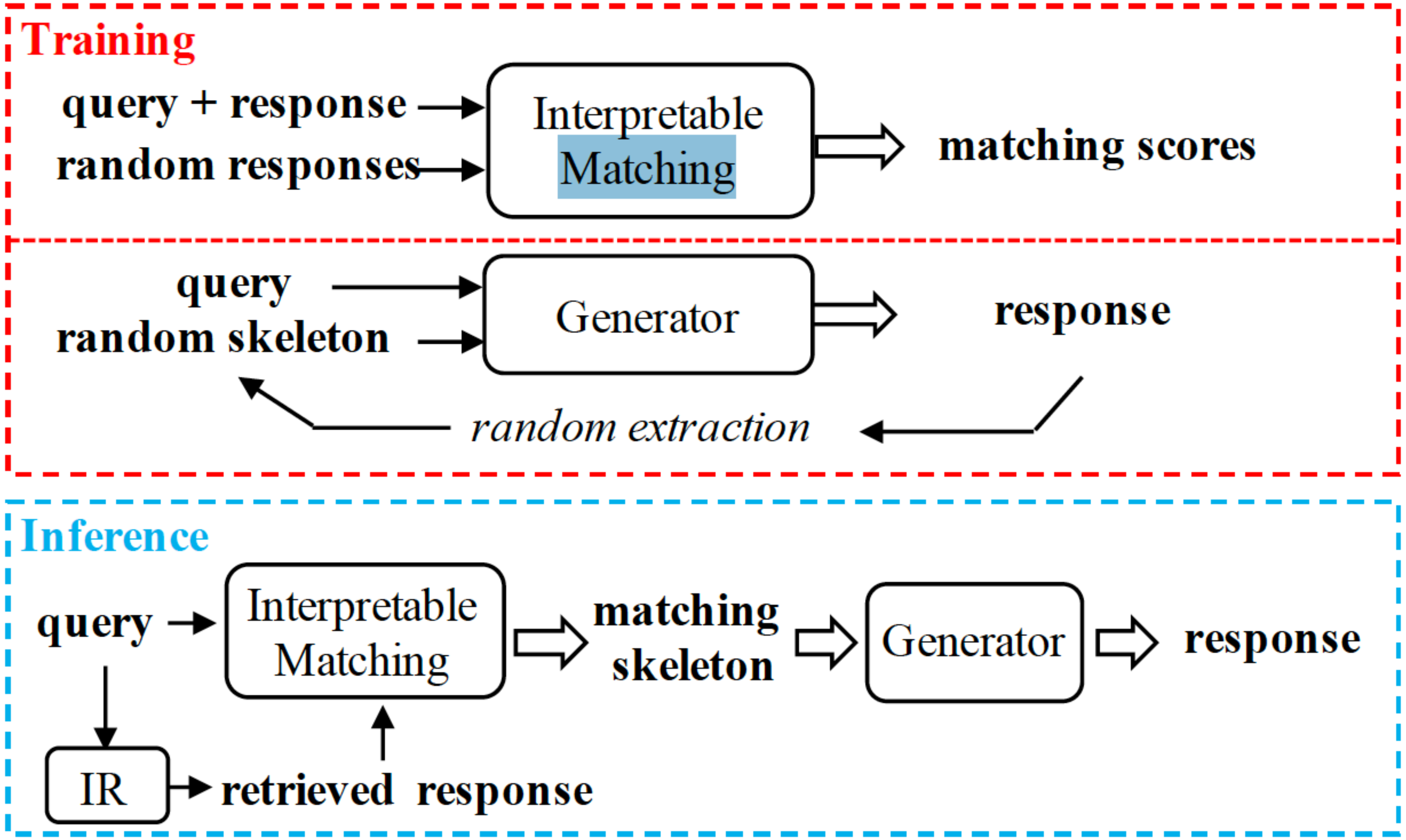


Figure 2: Flow charts during training and inference.

Model——matching model

给定query-response对，获取token-level匹配信息;

$$\omega_i = \frac{\exp(\mathbf{r}^w \cdot \mathbf{r}_i)}{\sum_{k=1}^{m} \exp(\mathbf{r}^w \cdot \mathbf{r}_k)}$$

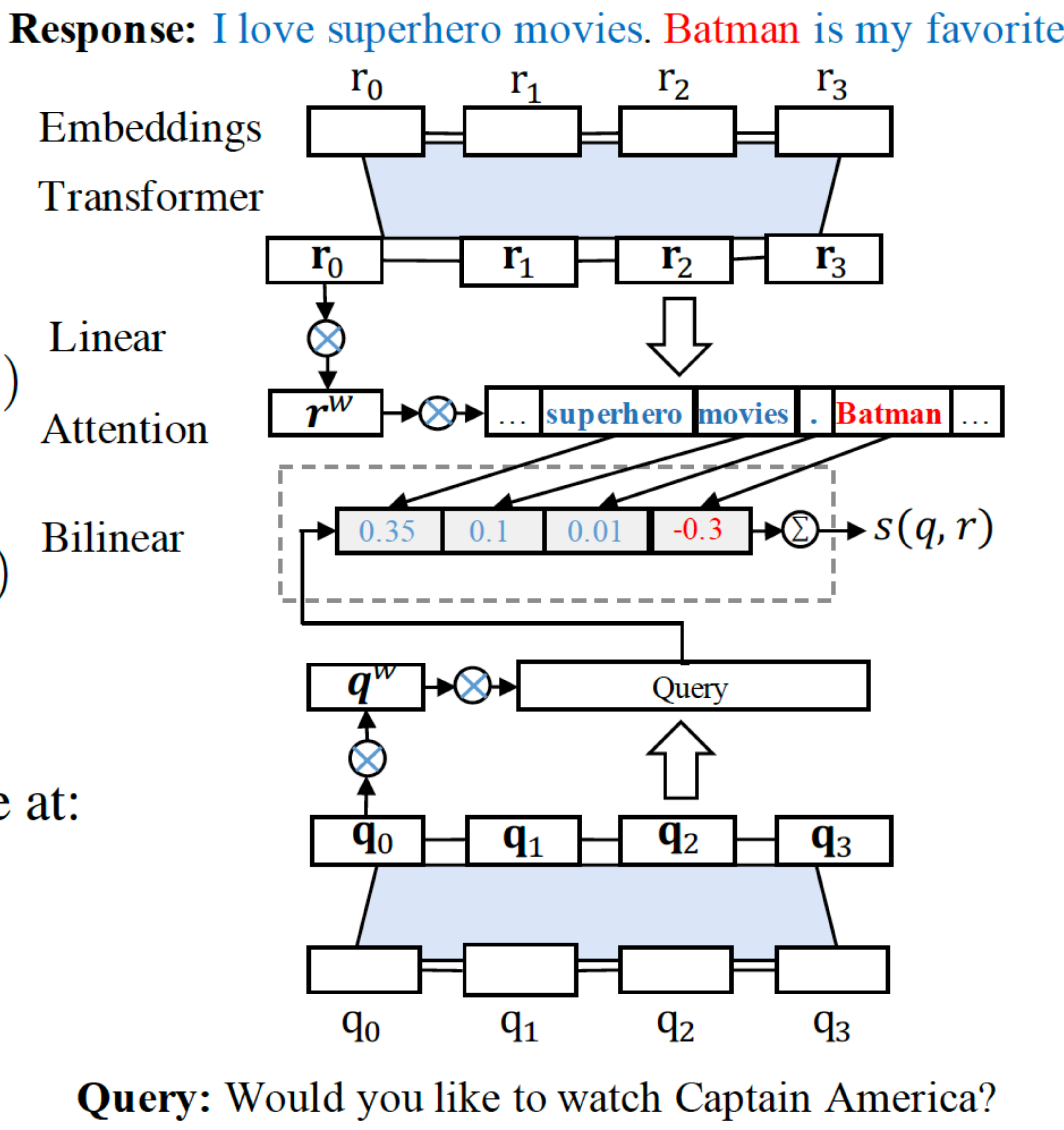
$$\mathbf{x}_r = \sum_{k=1}^{m} \omega_i(\mathbf{r}_i + \mathbf{e}_{r_i})$$

$$s(q,r) = \mathbf{x}_q{}^T W^s \mathbf{x}_r$$

$$\begin{aligned} s(q,r) &= \mathbf{x}_q{}^T W^s \mathbf{x}_r \\ &= \mathbf{x}_q{}^T W^s \sum_{k=1}^{m} \omega_k(\mathbf{r}_k + \mathbf{e}_{r_k}) \\ &= \sum_{k=1}^{m} \omega_k \mathbf{x}_q{}^T W^s(\mathbf{r}_k + \mathbf{e}_{r_k}) \end{aligned}$$

Let $s_k = \mathbf{x}_q{}^T W^s(\mathbf{r}_k + \mathbf{e}_{r_k})$, we arrive at:

$$s(q,r) = \sum_{k=1}^{m} \omega_k s_k$$



Training

每一个batch，随机取 M 个 query-response 对，两两之间进行打分，得到 score matrix S；

$S_{i,j}$ 表明第 i 个query和第 j 个response之间的匹配分数。

$$L(\theta) = -\sum_{k=1}^{M} \log \mathrm{softmax}(\mathbf{S}_{k:})_k$$

Model——skeleton-guided response generator

- All stop words in r are masked in advance. The rest tokens are masked at a mask rate γ. 90% of the time, γ is set to 0.7. 10% of the time, γ is uniformly sampled in the range of $[0, 1]$.
- Instead of always replacing the masked token with a special placeholder token, 20% of time, we replace the token with a random word uniformly sampled from the total vocabulary.
- At a chance of 10%, we randomly shuffle the word order in the training skeleton.

encoder for query q；

encoder for skeleton s；

decoder for response r

Experiment

单轮对话数据集

Models	Informativeness	Relevance	Fluency	Dist-1(%)	Dist-2(%)
Retrieval	2.65 (0.90)†	2.58 (0.86)	2.96 (0.72)	**49.10**	**84.19**
Seq2Seq	2.01 (0.65)	2.58 (0.53)	2.71 (0.43)	30.38	54.52
Seq2Seq-MMI	2.47 (0.70)	2.79 (0.67)	2.99 (0.61)	30.98	62.85
RetrieveNRefine^{++}	2.30 (0.79)	2.62 (0.63)	2.82 (0.51)	29.83	61.07
EditVec	2.29 (0.61)	2.62 (0.60)	2.83 (0.47)	35.30	67.57
Skeleton-Lex	2.45 (0.61)	2.80 (0.56)	2.99 (0.46)	25.70	56.61
Ours	**2.69** (0.87)	**3.11** (0.55)	**3.20** (0.55)	**49.01**	**80.36**

Table 1: Human scores on response quality, depicted in three aspects: informativeness, relevance, and fluency, with standard deviation in parentheses. Sign tests on human scores show that our method is significantly better than all other methods with p-value $<$0.01 with the only exception marked by †. We also present dist-1 and dist-2 for diversity assessment.

Experiment

Query	喜欢长头发的女生 I like girls with long hair
Retrieved response	可以 把 头发 后面 汤 大 卷 ， 前面 是 直 刘海 ， 这样 看 的 很 可爱 You can try perming the hair , hair with curly ends and straight bangs is very cute.
Ours	我也喜欢长**头发**的女生,**卷**了**直刘海**, 头发就不好看了 I also like girl with long **hair**, I think once the **straight bangs** are **curled**, it doesn't look good any more.
Seq2Seq-MMI	我也喜欢长头发的女生 I also like girls with long hair.
RetrieveNRefine^{++}	我喜欢长头发的女生 I like girls with long hair.
EditVec	我也喜欢长头发的女生 I also like girls with long hair.
Skeleton-Lex	我喜欢长头发的女生 I like girls with long hair.
Query	我提现怎么还没到 Why hasn't my withdrawal arrived yet?
Retrieved response	就是 提现 到 你 绑定 的 银行卡 上 了 Withdrawal is in the bound bank card .
Ours	你**提现**的时候**绑定**了**银行卡**吗 Have you **bounded** the **bank card** when **withdrawing** ?
Seq2Seq-MMI	我提现也到了 My withdrawal has arrived too.
RetrieveNRefine^{++}	你要支付宝干嘛 Why do you need Alipay?
EditVec	你是提现的吗 Do you want to withdraw?
Skeleton-Lex	你不是已经到了吗 Haven't you arrived ?

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Controlling Dialogue Generation with Semantic Exemplars

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Motivation

Current exemplar-based method:

1) 胡乱复制
2) 忽视样例

Context	My friends and I have started eating vegan food since yesterday.
Exemplar **Frames** **Responses**	Eggs are very beneficial for your body. FOOD USEFULNESS BODY-PARTS Vegan food can be good for your health. Vegetables can do wonders for your body Vegan food is very healthy.
Exemplar **Frames** **Responses**	I want to drink milk as well. DESIRING INGESTION FOOD You want to eat some vegan food? We eat a lot of vegetables. It's delicious. We like to eat organic food.

Table 1: EDGE generates responses to dialogue contexts by conditioning the response generation on the semantic frames of existing response exemplars to create coherent and controlled replies.

FrameNet

1. 重用 high-level semantic structure来组织 low-level response tokens，使其适应新的 dialogue context；
2. 帮助模型避免过拟合。

Model

TransferTransfo: 用以下两个目标函数微调GPT：

1) a language modeling objective;

2)a next-utterance classification objective.

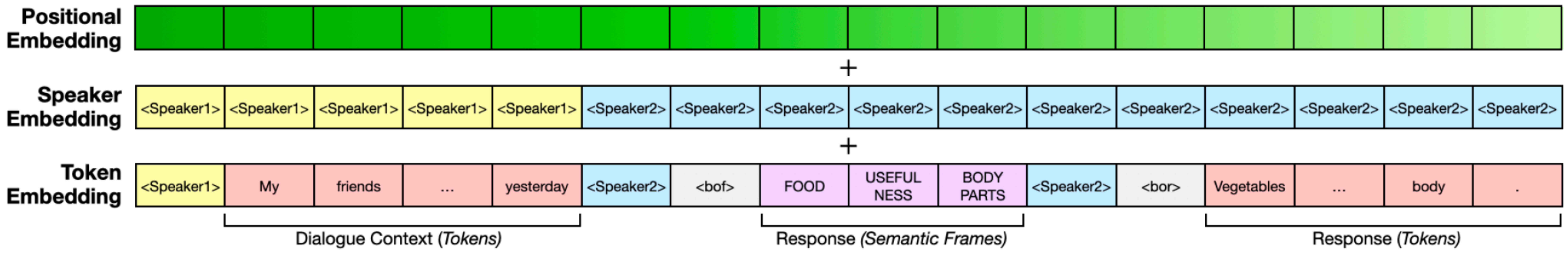

Figure 1: The input representation of our proposed approach. During training, EDGE conditions on the dialogue context and a noisy version of the ground truth response semantic frames to generate the ground truth response. During inference, we feed the context and the semantic frames from the response exemplars to generate a response.

Model——frame

open-sesame model(2017): F1 score 73.25% for frame target detection &

85.66% for frame identification.

frame检测模块准确率不高，为了让模型对于 遗失/错误检测 的frame更健壮：

1. 随机扔掉15%的frame；
2. 以10%的概率随机打乱frame的顺序；
3. 在随机的位置插入不相关的frame.

Experiment

open-domain 对话生成：Dailydialog 数据集

Model	Dist-2	Dist-3	MaUdE	Coherent	Fluent	Consistent	Interesting	Semantics
Retrieval	0.294	0.526	0.921	2.41	2.61	2.48	2.32	-
GPT2-Gen	0.249	0.494	0.905	2.42	2.55	2.41*	2.18*	-
LSTM-Tokens	0.182	0.380	0.890	2.04*	2.10*	2.11*	1.89*	2.17
LSTM-Frames	0.185	0.392	0.901	2.36*	2.30*	2.33*	1.97*	**2.29**
GPT2-Tokens	0.254	0.513	**0.927**	2.19*	2.47*	2.29*	2.11*	2.04*
EDGE (Ours)	**0.278**	**0.571**	0.922	**2.52**	**2.63**	**2.56**	**2.39**	2.24
Human	0.385	0.720	0.911	2.76	2.69	2.78	2.44	-

Table 2: Results for automatic (Dist-2, Dist-3, and MaUdE) and human (Coherent, Fluent, Consistent, Interesting, and Uses Semantics) evaluation on the Dailydialog corpus. Our model significantly outperforms other models (t-test comparison with EDGE, $p < 0.05$ indicated with *) on human-rated metrics and performs similarly to the Retrieval baseline and Ablation models in automatic metrics. We did not collect Uses Semantics for the Human, Retrieval and GPT2-Gen cases which do not condition on exemplars.

Experiment

Metric	1 Exemplar	5 Exemplars	10 Exemplars
		GPT2-Gen	
Dist-2	0.240	0.129	0.096
Dist-3	0.481	0.327	0.270
		LSTM-Tokens	
SemCov	0.347	0.354	0.360
Avg BLEU-2	0.216	0.214	0.214
Dist-2	0.184	0.104	0.080
Dist-3	0.387	0.267	0.223
		EDGE	
SemCov	**0.650**	**0.620**	**0.625**
Avg BLEU-2	**0.192**	**0.170**	**0.161**
Dist-2	**0.274**	**0.155**	**0.118**
Dist-3	**0.569**	**0.409**	**0.344**

Table 3: EDGE shows higher semantic coverage (SemCov) with the exemplar responses while showing lower lexical overlap (lower Avg BLEU-2). EDGE also achieves higher diversity (Dist-2,3).

Experiment

Context	*Human1*: they sell everything. *Human2*: well, i want chinese food.	*Human1*: actually i have a passion for chinese literature. *Human2*: you do?
Retrieved	well, what do you want to eat?	yes, reading is my hobby.
Frames	WHAT DESIRING INGESTION ?	YES LINGUISTIC-MEANING
GPT2-Gen	it's a good idea.	yes. i'm passionate.
LSTM-Tokens	well, what's the you do?	yes, i do.
LSTM-Frames	i hope so.	yes, i did.
GPT2-Tokens	i'm not sure what to get.	what are you interested in?
EDGE (Ours)	you want to eat something chinese?	yes. i studied chinese literature at university.
Context	*Human1*: jeff, i'm going to the supermarket. do you want to come with me? *Human2*: i think the supermarket is closed now.	*Human1*: did you go to the concert last weekend? *Human2*: no, i didn't. and you? was it good?
Retrieved	i know. i intent to go to the store today.	yes, i did. i enjoyed it a lot. there was a folk singer, a violinist and a pianist.
Frames	AWARENESS PURPOSE MOTION BUSINESSES TEMPORAL-COLLOCATION	YES EXPERIENCER-FOCUS DESTINY LOCATIVE -RELATION PEOPLE
GPT2-Gen	what a pity!	yes. i enjoyed it very much.
LSTM-Tokens	yes, i'm sorry to go with you.	yes, i did. i've got a singer, but i was the violinist.
LSTM-Frames	where is the market?	yes, i've been interested in a lot of people.
GPT2-Tokens	where is the supermarket?	i think you're right. the performance was very beautiful.
EDGE (Ours)	i know, but i'm planning to go to the bank today.	yes. i was very interested in the performance. i was in the audience and it was really packed.

Table 4: Sample model responses to dialogue contexts in the open-domain setting of Dailydialog conversations. The responses of all models except GPT2-Gen are conditioned on the Retrieved responses using either the retrieved response tokens or the extracted semantic frames (Frames). EDGE generates more coherent and interesting responses compared to the baselines, without directly copying tokens from the retrieved responses.